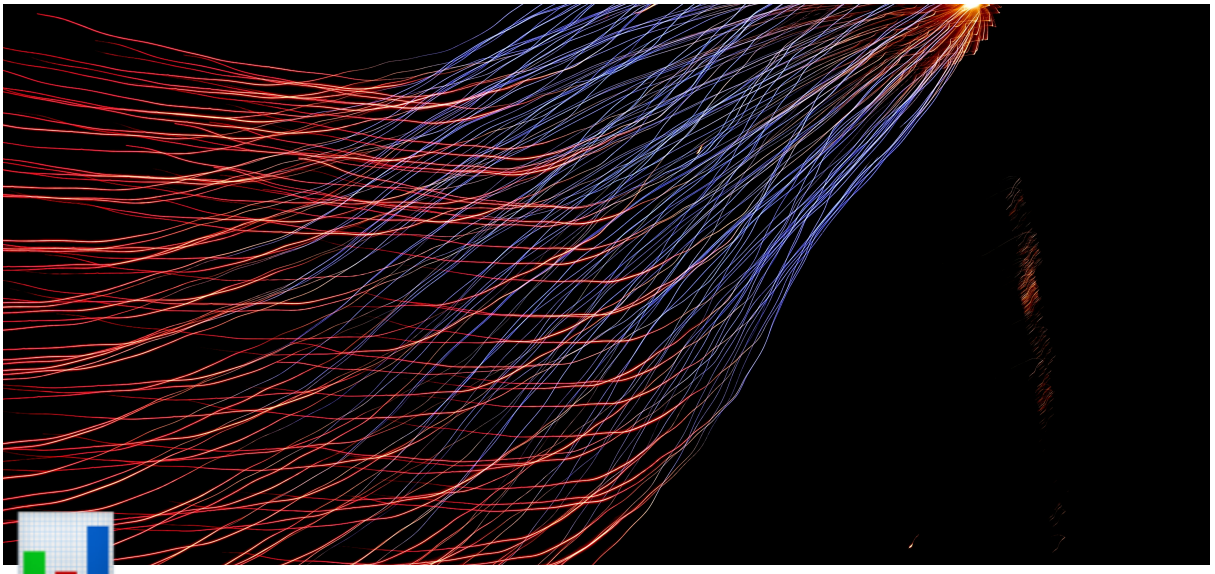

# PyCaret

| | |
|---|---|
| Created | @November 25, 2024 10:35 AM |
| Tags | |

# Inleiding

Voor project 4.0 zijn we bezig met een project voor Cipal Schaubroek. Hierbij hebben we de opdracht gekregen om oplossingen uit te werken om te helpen bij het beheer van het groeiende cameranetwerk. Een deel van de oplossing bestaat uit automatische interpretatie van meldingen dat de cameras terug sturen. Dit moet gebeuren doormiddel van ai. Daarom onderzoek ik in dit document Pycaret. Een end-to-end machine learning library.

# Pycaret?

Pycaret is designed to be an end-to-end machine learning library. This means that is not just made for one specific use case but rather for all your machine learning needs. Under this text is a list of stages that Pycaret has integrated tools for:

- **Data Preparation**: PyCaret can handle data preprocessing tasks such as missing value imputation, scaling, encoding categorical variables, and feature engineering. This is done using the setup function, which prepares the data for modeling.
- **Model Training**: PyCaret provides a simple interface to train multiple machine learning models with just a few lines of code. You can use functions like compare_model to train and evaluate different models quickly.
- **Model Evaluation**: After training, PyCaret offers various tools to evaluate model performance using metrics and visualizations. This helps in

understanding how well the models are performing.

- **Model Tuning**: PyCaret includes functionalities for hyperparameter tuning to optimize model performance.
- **Model Deployment**: Once a model is trained and evaluated, PyCaret can help deploy the model into production. It supports exporting models as APIs or saving them for later use.
- **Model Monitoring**: PyCaret integrates with tools like MLflow for tracking experiments and monitoring model performance over time.

# Pycaret facettes

## exploratory data analysis

Pycaret includes different functions for analysing your dataset(s). In the following section we will explore the the 8 functions that they provide for exploring your data easier.

> these are functions to be used on trained models

### plot_model

This function can be used for analysing the performance of a trained model on the *hold-out set. This function can be used with some parameters to change the resulting graph.

**standard example:**

```
# load dataset
from pycaret.datasets import get_data
diabetes = get_data('diabetes')

# init setup
from pycaret.classification import *
clf1 = setup(data = diabetes, target = 'Class variable')

# creating a model
lr = create_model('lr')
```

```
# plot model
plot_model(lr, plot = 'auc')
```

We first can change the output resolution for the output graphs using the `scale` parameter and later save the output using the 'save = true' parameter in the plot_model() function. Important to know, the library uses Yellowbrick for plotting, this means that all the arguments that you can pass to Yellowbricks visualiser are acceptable for Pycaret aswell. Lastly, you can use train data aswell by passing 'use_train_data=true' in the plot_model() function.

> Keep in mind, using train data where the model was already trained on may conclude to a biased result.

when passing plot='xxx' we should give a module for what we want to analyse. For a list of all the different modules, please reference the pycaret documentation with the following link.

link: https://pycaret.gitbook.io/docs/get-started/functions/analyze#examples-by-module

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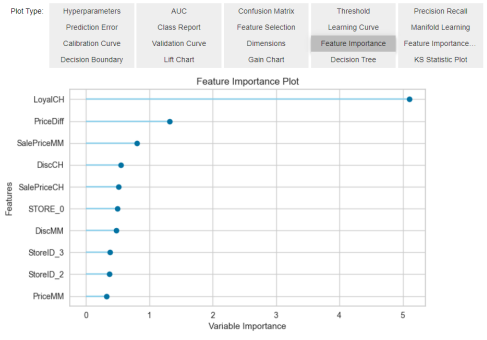
*A hold-out set is used to give a objective review of the model's performance during the training process.

## evaluate_model

this function is used for analysing the performance of the model as well but displays a user interface instead. It calls the plot_model user interface internally and can only be run in a jupyter notebook or similar invironment.

```
# load dataset
from pycaret.datasets import get
juice = get_data('juice')

# init setup
from pycaret.classification impo
exp_name = setup(data = juice,
```

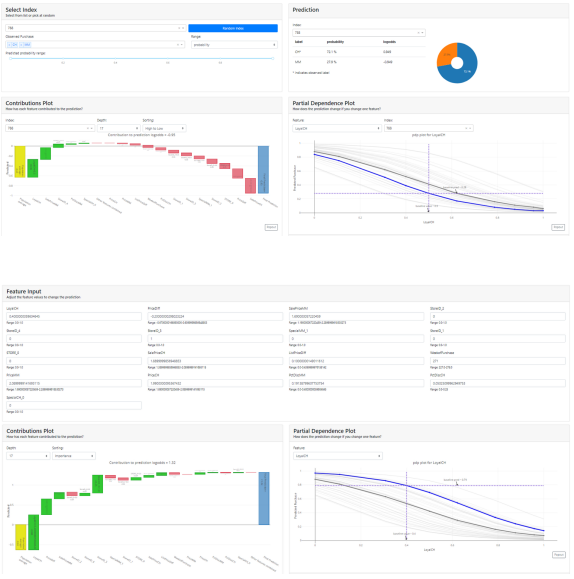


```
# create model
lr = create_model('lr')

# launch evaluate widget
evaluate_model(lr)
```

## dashboard

'Dashboard' function is used for generating interactive user interface dashboard. You can input certain values and the plots will change accordingly. This function uses ExplainerDashboard, this is another library used for building interactive dashboard.

```
# load dataset
from pycaret.datasets import
juice = get_data('juice')

# init setup
from pycaret.classification
exp_name = setup(data = juic

# train model
lr = create_model('lr')

# launch dashboard
dashboard(lr)
```



## check_fairness

This function is used to check the fairness of a model. It evaluates the model's predictions or decisions and sees if it impacts different groups of individuals. It helps insure that the model does not inherently have a bias towards a particular group. 'check_fairness' function gives back fairness-related metrics between different groups.

```
# load dataset
from pycaret.datasets import
income = get_data('income')

# init setup
from pycaret.classification
exp_name = setup(data = inco

# train model
lr = create_model('lr')

# check model fairness
lr_fairness = check_fairness
```


| sex | race | Samples | Accuracy | AUC | Recall | Precision | F1 | Kappa | MCC | Selection Rate |
|---|---|---|---|---|---|---|---|---|---|---|
| Female | Amer-Indian-Eskimo | 39 | 0.974359 | 0.875 | 0.75 | 1.0 | 0.857143 | 0.843373 | 0.853913 | 0.076923 |
| | Asian-Pac-Islander | 94 | 0.882979 | 0.687342 | 0.4 | 0.75 | 0.521739 | 0.462019 | 0.491733 | 0.085106 |
| | Black | 473 | 0.955603 | 0.751894 | 0.515152 | 0.772727 | 0.618182 | 0.595611 | 0.609441 | 0.046512 |
| | Other | 32 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.0625 |
| | White | 2523 | 0.923107 | 0.74021 | 0.505376 | 0.715736 | 0.592437 | 0.551373 | 0.561562 | 0.078082 |
| Male | Amer-Indian-Eskimo | 70 | 0.957143 | 0.825521 | 0.666667 | 0.8 | 0.727273 | 0.704225 | 0.707673 | 0.071429 |
| | Asian-Pac-Islander | 218 | 0.807339 | 0.763996 | 0.642857 | 0.725806 | 0.681818 | 0.544387 | 0.546449 | 0.284404 |
| | Black | 470 | 0.865957 | 0.713596 | 0.466667 | 0.736842 | 0.571429 | 0.496685 | 0.514902 | 0.121277 |
| | Other | 51 | 0.921569 | 0.68913 | 0.4 | 0.666667 | 0.5 | 0.460317 | 0.478051 | 0.058824 |
| | White | 5799 | 0.808243 | 0.755036 | 0.606337 | 0.748674 | 0.67003 | 0.536974 | 0.542904 | 0.260045 |

## get_leaderboard

This function simply returns a table with all the models that you are trying to evaluate and rank them by performance.

```
# load dataset
from pycaret.datasets import
diabetes = get_data('diabete

# init setup
from pycaret.classification
clf1 = setup(data = diabetes

# compare models
top3 = compare_models(n_sele

# tune top 3 models
tuned_top3 = [tune_model(i)

# ensemble top 3 tuned model
ensembled_top3 = [ensemble_m
```

| Index | Model Name | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Logistic Regression | (DataTypes_Auto_infer(categorical_features=[]... | 0.7598 | 0.8143 | 0.5229 | 0.6884 | 0.5875 | 0.4230 | 0.4355 |
| 1 | K Neighbors Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7321 | 0.7723 | 0.5291 | 0.6136 | 0.5629 | 0.3723 | 0.3780 |
| 2 | Naive Bayes | (DataTypes_Auto_infer(categorical_features=[]... | 0.6725 | 0.7161 | 0.1542 | 0.5483 | 0.2381 | 0.0991 | 0.1377 |
| 3 | Decision Tree Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.6688 | 0.6322 | 0.5275 | 0.5062 | 0.5077 | 0.2606 | 0.2675 |
| 4 | SVM - Linear Kernel | (DataTypes_Auto_infer(categorical_features=[]... | 0.5715 | 0.0000 | 0.5729 | 0.3904 | 0.4177 | 0.1314 | 0.1526 |
| 5 | Ridge Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7561 | 0.0000 | 0.4886 | 0.7045 | 0.5676 | 0.4056 | 0.4247 |
| 6 | Random Forest Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7506 | 0.8116 | 0.5062 | 0.6629 | 0.5700 | 0.3993 | 0.4089 |
| 7 | Quadratic Discriminant Analysis | (DataTypes_Auto_infer(categorical_features=[]... | 0.5195 | 0.5592 | 0.5788 | 0.3737 | 0.4039 | 0.0636 | 0.0733 |
| 8 | Ada Boost Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7449 | 0.7787 | 0.5735 | 0.6253 | 0.5960 | 0.4104 | 0.4127 |
| 9 | Gradient Boosting Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7300 | 0.8048 | 0.5565 | 0.5940 | 0.5694 | 0.3744 | 0.3784 |
| 10 | Linear Discriminant Analysis | (DataTypes_Auto_infer(categorical_features=[]... | 0.7487 | 0.8099 | 0.4830 | 0.6836 | 0.5580 | 0.3896 | 0.4064 |
| 11 | Extra Trees Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7432 | 0.7885 | 0.4892 | 0.6545 | 0.5566 | 0.3808 | 0.3913 |
| 12 | Extreme Gradient Boosting | (DataTypes_Auto_infer(categorical_features=[]... | 0.7301 | 0.7752 | 0.5631 | 0.5937 | 0.5734 | 0.3776 | 0.3807 |
| 13 | Light Gradient Boosting Machine | (DataTypes_Auto_infer(categorical_features=[]... | 0.7319 | 0.7848 | 0.5565 | 0.6055 | 0.5747 | 0.3802 | 0.3846 |
| 14 | CatBoost Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7506 | 0.8224 | 0.5516 | 0.6424 | 0.5897 | 0.4128 | 0.4179 |
| 15 | Dummy Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.6723 | 0.5000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 16 | Logistic Regression | (DataTypes_Auto_infer(categorical_features=[]... | 0.7691 | 0.8175 | 0.5346 | 0.7108 | 0.6030 | 0.4451 | 0.4590 |
| 17 | Ridge Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7580 | 0.0000 | 0.4941 | 0.7056 | 0.5729 | 0.4112 | 0.4294 |
| 18 | Random Forest Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7727 | 0.8152 | 0.8056 | 0.6206 | 0.6989 | 0.5216 | 0.5357 |
| 19 | Logistic Regression | (DataTypes_Auto_infer(categorical_features=[]... | 0.7543 | 0.8194 | 0.5288 | 0.6629 | 0.5837 | 0.4133 | 0.4215 |
| 20 | Ridge Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7653 | 0.7441 | 0.4886 | 0.7156 | 0.5725 | 0.4205 | 0.4394 |
| 21 | Random Forest Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7653 | 0.8179 | 0.7719 | 0.6145 | 0.6819 | 0.4998 | 0.5110 |
| 22 | Voting Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7636 | 0.0000 | 0.5288 | 0.7043 | 0.5955 | 0.4333 | 0.4481 |
| 23 | Stacking Classifier | (DataTypes_Auto_infer(categorical_features=[]... | 0.7580 | 0.8223 | 0.5180 | 0.6767 | 0.5828 | 0.4173 | 0.4271 |

```
# blender
blender = blend_models(tuned

# stacker
stacker = stack_models(tuned

# check leaderboard
get_leaderboard()
```

## assign_model

This function gives back a table and assigns labels to the training dataset using the trained model. This is available for following *modules:

- clustering
- anomaly detection
- Natural Language Processing

```
# load dataset
from pycaret.datasets import
jewellery = get_data('jewell

# init setup
from pycaret.clustering impo
# or this when using anomaly
# from pycaret.clustering im

clu1 = setup(data = jeweller

# train a model
kmeans = create_model('kmean

# assign model
assign_model(kmeans)
```

| | Age | Income | Spending Score | Savings | Cluster |
|---|---|---|---|---|---|
| 0 | 58 | 77769 | 0.791329 | 6559.829923 | Cluster 2 |
| 1 | 59 | 81799 | 0.791082 | 5417.661426 | Cluster 2 |
| 2 | 62 | 74751 | 0.702657 | 9258.992965 | Cluster 2 |
| 3 | 59 | 74373 | 0.765680 | 7346.334504 | Cluster 2 |
| 4 | 87 | 17760 | 0.348778 | 16869.507130 | Cluster 1 |
| ... | ... | ... | ... | ... | ... |
| 500 | 28 | 101206 | 0.387441 | 14936.775389 | Cluster 3 |
| 501 | 93 | 19934 | 0.203140 | 17969.693769 | Cluster 1 |
| 502 | 90 | 35297 | 0.355149 | 16091.401954 | Cluster 1 |
| 503 | 91 | 20681 | 0.354679 | 18401.088445 | Cluster 1 |
| 504 | 89 | 30267 | 0.289310 | 14386.351880 | Cluster 1 |

505 rows × 5 columns

| | Col1 | Col2 | Col3 | Col4 | Col5 | Col6 | Col7 | Col8 | Col9 | Col10 | Anomaly | Anomaly_Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.263995 | 0.764929 | 0.138424 | 0.935242 | 0.605867 | 0.518790 | 0.912225 | 0.608234 | 0.723782 | 0.733591 | 0 | -0.023131 |
| 1 | 0.546092 | 0.653975 | 0.065575 | 0.227772 | 0.845269 | 0.837066 | 0.272379 | 0.331679 | 0.429297 | 0.367422 | 0 | -0.077484 |
| 2 | 0.336714 | 0.538842 | 0.192801 | 0.553563 | 0.074515 | 0.332993 | 0.365792 | 0.861309 | 0.899017 | 0.088600 | 0 | -0.002603 |
| 3 | 0.092108 | 0.995017 | 0.014465 | 0.176371 | 0.241530 | 0.514724 | 0.562208 | 0.158963 | 0.073715 | 0.208463 | 1 | 0.060657 |
| 4 | 0.325261 | 0.805968 | 0.957033 | 0.331665 | 0.307923 | 0.355315 | 0.501899 | 0.558449 | 0.885169 | 0.182754 | 0 | -0.011531 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 995 | 0.305055 | 0.656837 | 0.331665 | 0.822525 | 0.907127 | 0.882276 | 0.855732 | 0.584786 | 0.808640 | 0.242762 | 0 | -0.076773 |
| 996 | 0.812627 | 0.864258 | 0.616604 | 0.167966 | 0.811223 | 0.938071 | 0.418462 | 0.472306 | 0.348347 | 0.671129 | 0 | -0.084505 |
| 997 | 0.250967 | 0.138627 | 0.919703 | 0.461234 | 0.886555 | 0.869888 | 0.800908 | 0.530324 | 0.779433 | 0.234952 | 0 | -0.054988 |
| 998 | 0.502436 | 0.936820 | 0.580062 | 0.540773 | 0.151995 | 0.059452 | 0.225220 | 0.242755 | 0.279385 | 0.538755 | 0 | -0.087168 |
| 999 | 0.457991 | 0.017755 | 0.714113 | 0.125992 | 0.063316 | 0.154739 | 0.922974 | 0.692299 | 0.816777 | 0.307592 | 0 | -0.016641 |

1000 rows × 12 columns

*modules: these are machine learning use-cases that are supported in PyCaret

# data preprocessing

## Data Preparation

- **Missing values**: fill in empty records encoded as blanks or NaN (not a number).
- **Data Types**: it automatically detects the data types of each feature
- **One-Hot Encoding**: it gives labels like ordinal or nominal instead of continuous numbers
- **Ordinal Encoding**: it encodes the categorical features with a natural hierarchy differently

  ex. labels like: Low, Medium, High,...
- **Cardinal Encoding**: this encoding should be used with high cardinality categorical features in datasets
- **Target Imbalance**: when the training dataset has unequal distribution of target class
- **Remove Outliers**: you can remove outliers from the training dataset

## Scale and Transform

- **Normalize**
- **Feature Transform**: change the shape of the distribution of features
- **Target Transform**: change the shape of the distribution of the target variables

## Feature Engineering

- **Feature Interaction**: Combining two features through mathematical operations can often explain variance better than the features individually.
- **Polynomial Features**: Introduces non-linearity by creating higher-order terms of existing features.
- **Group Features**: Calculate group statistics (mean, median, variance, standard deviation) for related features.
- **Feature Binning**: Converts continuous variables into categorical ones by dividing them into predefined intervals (bins).

- **Combine Rare Levels**: Merges rare levels in categorical features with high cardinality to reduce sparsity.
- **Create Clusters**: Uses unsupervised ML techniques to create new features based on clusters in the data.

### Feature Selection

- **Feature Selection**: Identifies the most relevant features for predicting the target variable, reducing overfitting, improving accuracy, and speeding up training.
- **Remove Multicollinearity**: Eliminates features that are highly linearly correlated with each other to avoid redundancy and instability.
- **Principal Component Analysis (PCA)**: An unsupervised technique to reduce dimensionality by compressing the feature space while preserving variance.
- **Ignore Low Variance**: Discards features with skewed distributions or levels dominated by one category, as they provide minimal predictive power.

### Other Setup Parameters

- **Required Parameters**:
  - **Data**: The dataset to be used.
  - **Target Variable**: The name of the target column.
- **Experiment Logging**: Tracks metrics, hyperparameters, and artifacts automatically using **MLflow**.
- **Model Selection**: Allows configuration of parameters that influence the model selection process, separate from data preprocessing.
- **Miscellaneous Parameters**: Control settings like GPU usage for training and verbosity levels of the experiment.

## model training

### Compare_models

This function trains and evaluates the performance of all estimators available in the model library using cross-validation. The output of this function is a scoring grid with average cross-validated scores.

```
# load dataset
from pycaret.datasets import
diabetes = get_data('diabete

# init setup
from pycaret.classification
clf1 = setup(data = diabetes

# compare models
best = compare_models()
```

| | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC | TT (Sec) |
|---|---|---|---|---|---|---|---|---|---|
| catboost | CatBoost Classifier | 0.7672 | 0.8324 | 0.5681 | 0.6901 | 0.6177 | 0.4537 | 0.4616 | 0.6180 |
| rf | Random Forest Classifier | 0.7635 | 0.8121 | 0.5184 | 0.7051 | 0.5904 | 0.4315 | 0.4452 | 0.0720 |
| et | Extra Trees Classifier | 0.7597 | 0.7945 | 0.5132 | 0.7024 | 0.5851 | 0.4236 | 0.4378 | 0.0650 |
| lr | Logistic Regression | 0.7526 | 0.8175 | 0.5243 | 0.6701 | 0.5806 | 0.4115 | 0.4211 | 0.7690 |
| knn | K Neighbors Classifier | 0.7525 | 0.7543 | 0.5740 | 0.6572 | 0.6077 | 0.4290 | 0.4346 | 0.0090 |
| xgboost | Extreme Gradient Boosting | 0.7502 | 0.8060 | 0.6178 | 0.6386 | 0.6236 | 0.4374 | 0.4413 | 0.1030 |
| ridge | Ridge Classifier | 0.7490 | 0.0000 | 0.5132 | 0.6660 | 0.5719 | 0.4011 | 0.4114 | 0.0030 |
| lda | Linear Discriminant Analysis | 0.7490 | 0.8112 | 0.5298 | 0.6586 | 0.5791 | 0.4059 | 0.4144 | 0.0040 |
| lightgbm | Light Gradient Boosting Machine | 0.7448 | 0.8053 | 0.6009 | 0.6324 | 0.6109 | 0.4220 | 0.4268 | 0.0530 |
| gbc | Gradient Boosting Classifier | 0.7411 | 0.8186 | 0.5515 | 0.6403 | 0.5844 | 0.3995 | 0.4067 | 0.0310 |
| ada | Ada Boost Classifier | 0.7392 | 0.7894 | 0.5406 | 0.6323 | 0.5789 | 0.3928 | 0.3976 | 0.0270 |
| dt | Decision Tree Classifier | 0.7058 | 0.6705 | 0.5629 | 0.5609 | 0.5583 | 0.3388 | 0.3411 | 0.0040 |
| dummy | Dummy Classifier | 0.6629 | 0.5000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0030 |
| nb | Naive Bayes | 0.6610 | 0.7321 | 0.2260 | 0.5176 | 0.3045 | 0.1245 | 0.1477 | 0.0040 |
| qda | Quadratic Discriminant Analysis | 0.5201 | 0.5868 | 0.6035 | 0.3977 | 0.4553 | 0.0870 | 0.0692 | 0.0050 |
| svm | SVM - Linear Kernel | 0.5197 | 0.0000 | 0.5000 | 0.2441 | 0.3097 | 0.0211 | 0.0194 | 0.0050 |

## Create_model

unction trains and evaluates the performance of a given estimator using cross-validation. The output of this function is a scoring grid with CV scores by fold.

```
# load dataset
from pycaret.datasets import
diabetes = get_data('diabete

# init setup
from pycaret.classification
clf1 = setup(data = diabetes

# train logistic regression
lr = create_model('lr')
```

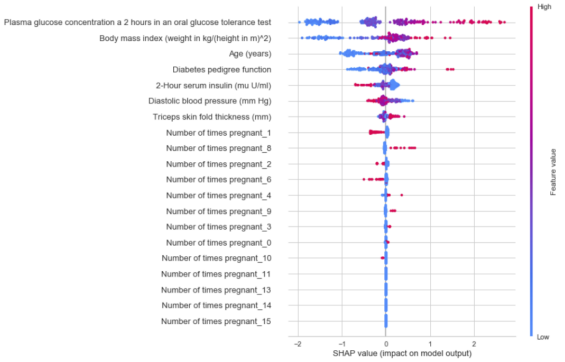
| | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|
| 0 | 0.8148 | 0.8827 | 0.5263 | 0.9091 | 0.6667 | 0.5507 | 0.5902 |
| 1 | 0.8148 | 0.8451 | 0.5263 | 0.9091 | 0.6667 | 0.5507 | 0.5902 |
| 2 | 0.7778 | 0.8556 | 0.6842 | 0.6842 | 0.6842 | 0.5128 | 0.5128 |
| 3 | 0.6296 | 0.6737 | 0.3684 | 0.4667 | 0.4118 | 0.1469 | 0.1491 |
| 4 | 0.7037 | 0.7865 | 0.5263 | 0.5882 | 0.5556 | 0.3344 | 0.3355 |
| 5 | 0.8148 | 0.8932 | 0.6316 | 0.8000 | 0.7059 | 0.5735 | 0.5820 |
| 6 | 0.7778 | 0.8406 | 0.6316 | 0.7059 | 0.6667 | 0.5008 | 0.5025 |
| 7 | 0.8113 | 0.8190 | 0.5556 | 0.8333 | 0.6667 | 0.5423 | 0.5640 |
| 8 | 0.7736 | 0.8607 | 0.6842 | 0.6842 | 0.6842 | 0.5077 | 0.5077 |
| 9 | 0.7925 | 0.8901 | 0.5789 | 0.7857 | 0.6667 | 0.5210 | 0.5338 |
| Mean | 0.7711 | 0.8347 | 0.5713 | 0.7366 | 0.6375 | 0.4741 | 0.4868 |
| SD | 0.0570 | 0.0621 | 0.0896 | 0.1329 | 0.0842 | 0.1259 | 0.1330 |

# model explainability

## interpret_model

this function is used for analysing the predictions generated by the model. Most of the graphs are based on ‘Shapley Additive exPlanations’ or SHAP. It is uses a game theory approach to explain the output of machine learning models.

```
# load dataset
from pycaret.datasets import
diabetes = get_data('diabete

# init setup
from pycaret.classification
clf1 = setup(data = diabetes

# creating a model
xgboost = create_model('xgbo

# interpret model
interpret_model(xgboost)
```




Just like with the function ‘model_plot’ you can use ‘save=true’ as a parameter to save the output as png and change te plot type with ‘plot=xxx’. The following plots can be displayed:

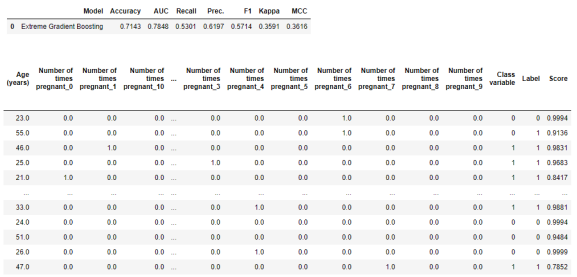
- **correlation**: Helps in understanding how features are related to each other and to the target variable. Strong correlations can indicate multicollinearity, which might affect the model's performance.
- **partial dependency plot:** Useful for understanding the relationship between a feature and the target variable, while averaging out the effects of all other features.
- **Morris sensitivity Analysis:** Helps in identifying which features have the most significant impact on the model's output, which is crucial for model interpretation and feature selection.
- **Permutation Feature Importance:** Useful for understanding the contribution of each feature to the model's predictions. It is model-agnostic and can be applied to any machine learning model.
- **Reason Plot:** Helps in explaining why the model made a specific prediction for a particular instance, which is important for model transparency and trust.

# Deployment

## predict_model

this function generates labels using a trained model

```
# load dataset
from pycaret.datasets import
diabetes = get_data('diabete

# init setup
from pycaret.classification
clf1 = setup(data = diabetes

# create a model
xgboost = create_model('xgbo

# predict on hold-out
predict_model(xgboost)
```



| | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|---|
| 0 | Extreme Gradient Boosting | 0.7143 | 0.7848 | 0.5301 | 0.6197 | 0.5714 | 0.3591 | 0.3616 |

| Age (years) | Number of times pregnant_0 | Number of times pregnant_1 | Number of times pregnant_10 | ... | Number of times pregnant_3 | Number of times pregnant_4 | Number of times pregnant_5 | Number of times pregnant_6 | Number of times pregnant_7 | Number of times pregnant_8 | Number of times pregnant_9 | Class variable | Label | Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 23.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0 | 0 | 0.9994 |
| 55.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0 | 1 | 0.9136 |
| 46.0 | 0.0 | 1.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1 | 1 | 0.9831 |
| 25.0 | 0.0 | 0.0 | 0.0 | ... | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1 | 1 | 0.9683 |
| 21.0 | 1.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1 | 1 | 0.8417 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 33.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1 | 1 | 0.9881 |
| 24.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0 | 0.9994 |
| 51.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0 | 0.9484 |
| 26.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0 | 0.9999 |
| 47.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 1 | 1 | 0.7852 |

## Finalize_model

This function trains a given model on the entire dataset including the hold-out set.

```
# load dataset
from pycaret.datasets import get_data
diabetes = get_data('diabetes')

# init setup
from pycaret.classification import *
clf1 = setup(data = diabetes, target = 'Class variable')

# create a model
rf = create_model('rf')

# finalize a model
finalize_model(rf)
```

## Deploy_model

deploys entire ML pipeline on the cloud

```
# load dataset
from pycaret.datasets import get_data
diabetes = get_data('diabetes')

# init setup
from pycaret.classification import *
clf1 = setup(data = diabetes, target = 'Class variable')

# create a model
lr = create_model('lr')

# finalize a model
final_lr = finalize_model(lr)

# deploy a model
deploy_model(final_lr, model_name = 'lr_aws', platform = 'aws
```

**Services**

- **AWS (amazon web services) environment variables**
  - AWS Access Key ID
  - AWS Secret Key Access
  - Default Region Name (can be seen under Global settings on your AWS console)
  - Default output format (must be left blank)
- **GCP (google cloud platform)**
  - the project must be created using the command-line or GCP console. Once the project is created, you must create a service account and download the service account key as a JSON file to set environment variables in your local environment.
- **Azure**
  - environment variables for the connection string must be set in your local environment. Go to settings of storage account on Azure portal to access the connection string required.

## save_model

This function saves the transformation pipeline and a trained model object into the current working directory as a pickle file for later use.

```
# load dataset
from pycaret.datasets import get_data
diabetes = get_data('diabetes')

# init setup
from pycaret.classification import *
clf1 = setup(data = diabetes, target = 'Class variable')

# create a model
dt = create_model('dt')

# save pipeline
save_model(dt, 'dt_pipeline')
```

## check_drift

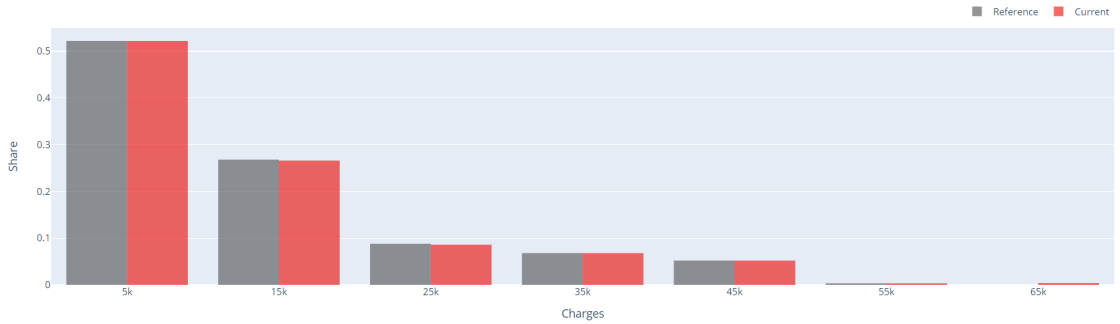
generates a drift report file. Model drift refers to the degradation of machine learning model performance due to changes in data or in the relationships between input and output variables. Model drift—also known as model decay—can negatively impact model performance, resulting in faulty decision-making and bad predictions.

```
# load dataset
from pycaret.datasets import get_data
data = get_data('insurance')

# generate drift report
check_drift(reference_data = data.head(500), current_data = d
```

Drift is detected for 0.00% of features (0 out of 7). Dataset Drift is NOT detected.

| Feature | Type | Reference Distribution | Current Distribution | Data Drift | Stat Test | Drift Score |
|---|---|---|---|---|---|---|
| charges | num | | | Not Detected | K-S p_value | 0.770437 |
| children | num | | | Not Detected | K-S p_value | 0.935112 |
| sex | cat | | | Not Detected | Z-test p_value | 0.89933 |
| smoker | cat | | | Not Detected | Z-test p_value | 0.64363 |
| region | cat | | | Not Detected | chi-square p_value | 0.630943 |
| age | num | | | Not Detected | K-S p_value | 0.329358 |
| bmi | num | | | Not Detected | K-S p_value | 0.172556 |

Target Drift: detected, drift score=0.0 (chi-square p_value)




## convert_model

This function transpiles the trained machine learning model's decision function in different programming languages. Useful if you want to deploy models into environments where you can't install your normal Python stack to support model inference.

```
# load dataset
from pycaret.datasets import get_data
juice = get_data('juice')

# init setup
from pycaret.classification import *
exp_name = setup(data = juice,  target = 'Purchase')

# train a model
lr = create_model('lr')
```

```
# convert a model
convert_model(lr, 'java')
```

## create_api

This function takes an input model and creates a POST API for inference. It only creates the API and doesn't run it automatically. To run the API, you must run the Python file using

```
# load dataset
from pycaret.datasets import get_data
juice = get_data('juice')

# init setup
from pycaret.classification import *
exp_name = setup(data = juice,  target = 'Purchase')

# train a model
lr = create_model('lr')

# create api
create_api(lr, 'lr_api')

# run api
!python lr_api.py
```

## create_docker

This function creates a Dockerfile and requirements.txt for productionalizing API end-point.

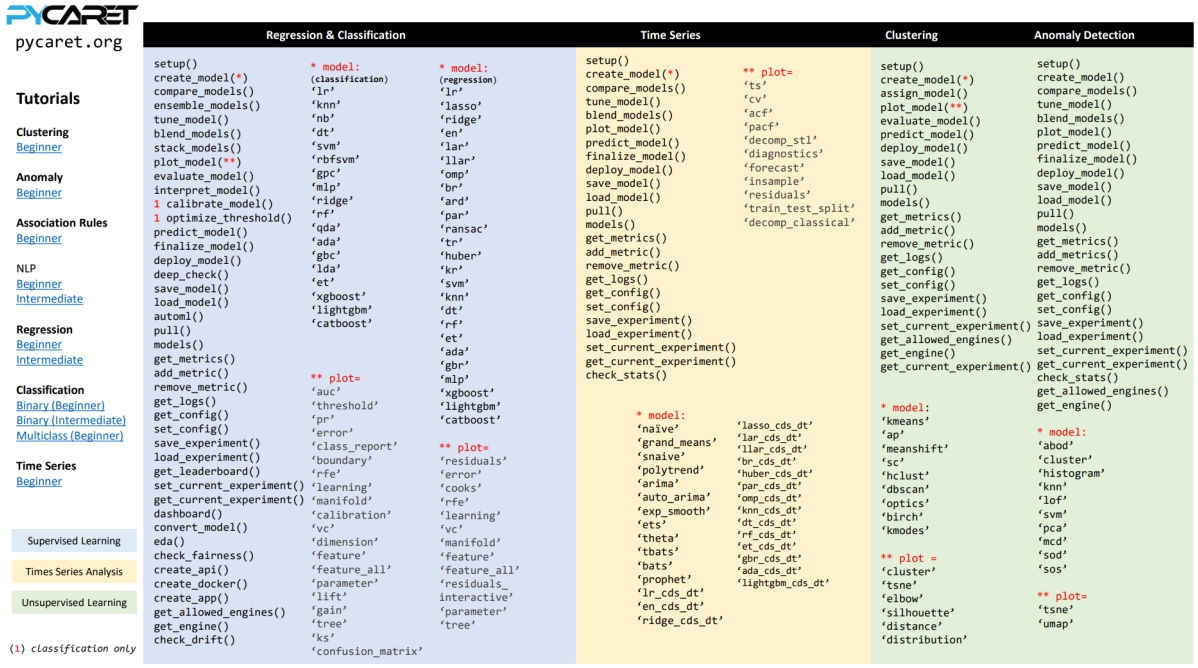
```
# load dataset
from pycaret.datasets import get_data
juice = get_data('juice')

# init setup
from pycaret.classification import *
exp_name = setup(data = juice,  target = 'Purchase')
```

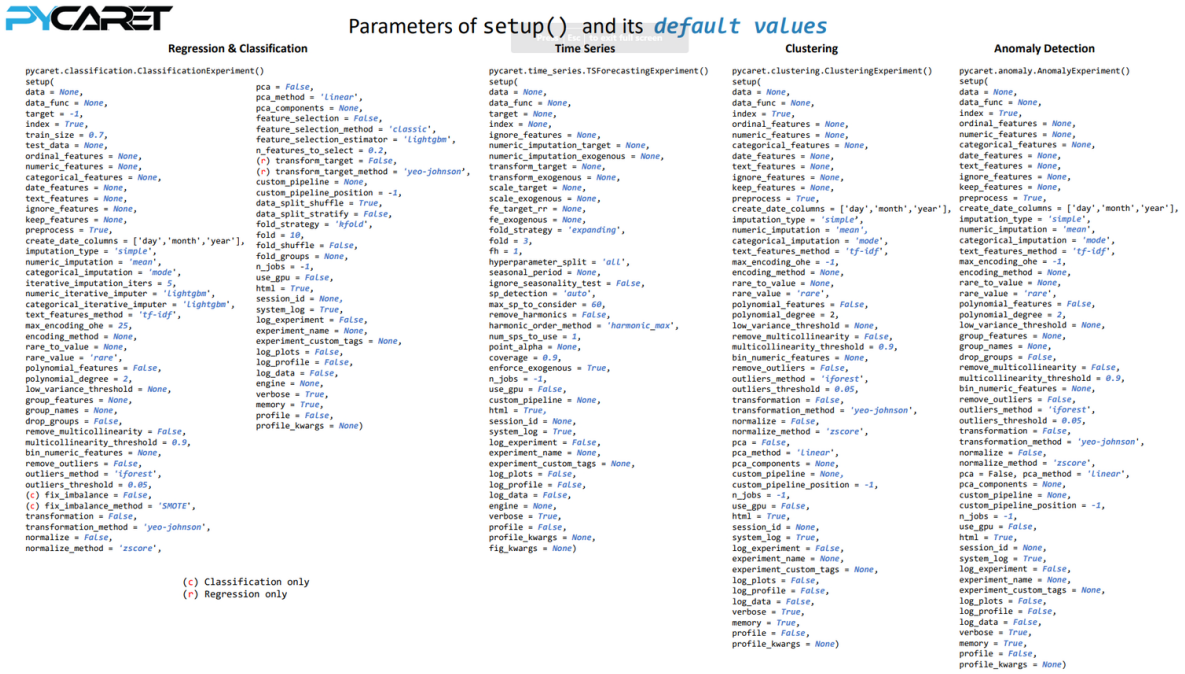
```
# train a model
lr = create_model('lr')

# create api
create_api(lr, 'lr_api')

# create docker
create_docker('lr_api')
```

# License

Pycaret is distributed under the MIT license which means you can use pycaret free of charge and are allowed to sell.

# cheat sheet






# Conclusie

Op basis van mijn onderzoek naar Pycaret kan ik afleiden dat deze end-to-end machine learning library een waardevolle tool is voor ons project bij Cipal Schaubroek. Pycaret biedt een uitgebreide set functies die ons team in staat stelt om efficiënt en effectief met machine learning te werken binnen het beperkte tijdsbestek van drie weken. Met name de **evaluate_model**-functie zal ons helpen om snel de meest geschikte modellen voor onze dataset te identificeren, wat cruciaal is voor de automatische interpretatie van camerameldingen. Daarnaast stelt de **create_api**-functie ons in staat om op een versnelde manier een API te ontwikkelen, waarmee de integratie met het app-team soepeler kan verlopen.